Recognition of Brain Tumors Using Radon Transform and Gray Level Co-Occurrence Matrix Algorithm

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Abstract: The field of recognizing brain tumors in recent years has received wide attention by researchers due to the rapid spread of the disease. In this paper, brain tumors (normal, glioma and meningioma) were recognized by the proposed networks (Support Vector Machine (SVM), Multilayer Perceptron Neural Network (MLPNN) and Radial Basis Function neural network (RBFNN)). The dataset is divided into two parts: 450 MRI images for the training phase and 240 for the testing phase. Pre-processing was applied to the input images by converting the images to grayscale and removing noise on them by median filter. Then, the texture features of MRI images were extracted using Gray Level Co-Occurrence Matrix algorithm after radon transformation. The extracted texture features were passed to the proposed networks for classification and recognition of tumors. The technique of extracting brain tumors from the magnetic resonance image was added by segmentation algorithm and morphology operations on the images. The performance of (SVM, MLPNN and RBFNN) was measured based on sensitivity, specificity, and accuracy and the best results obtained by SVM with a quadratic kernel function were 98.45, 98.97, and 98.71 for sensitivity, specificity, and accuracy, respectively.

Keywords: multilayer perceptron neural network, Support vector machine, radial basis function neural network, gray level co-occurrence matrix, Radon transform, magnetic resonance imaging.

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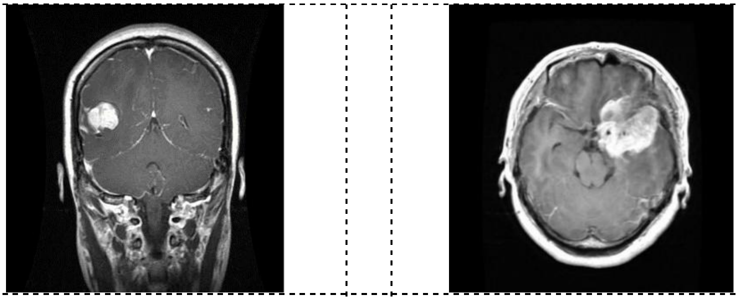
1. Introduction

Recently, cancers have become one of the complex medical problems that need great attention by researchers and link them to the field of computer. One of these diseases is brain tumor. Brain tumor is one of the most complex diseases, knowing that there are many studies that have made progress in finding solutions to this disease. The number of brain tumors in the Americas is estimated at 43,800 per year, and the number of malignant tumors is 18,500 [1]. Brain cancer can be defined as an abnormal growth of cells inside the brain or skull [2]. Tumors can also be classified into benign tumors and malignant tumors. Malignant tumors can be classified into primary or secondary tumors. The primary tumor consists of the cells of that organ in which the tumor is located. The secondary tumor consists of cells belonging to different other parts of the body [3]. There are several types of brain tumors as shown in figure 1, the most common being glioma and meningioma [4]. To diagnose brain cancer, it is done with the help of a computer by analyzing CT and MRI images, which give comprehensive information about the nature of the tumor.



a) Glioma **b) Meningioma**

Figure 1. Brain tumors

One of the main problems in the research was to obtain high accuracy in the analysis of the images and extract the important features and then classify them. them. It is known that classical techniques take longer time to identify images of cancerous diseases and require a large memory to save the extracted features and also the accuracy of recognition is weak, so it was necessary to overcome this problem by using modern algorithms and techniques to analyze and classify images. Recently, modern technologies such as artificial intelligence have been used to identify brain cancers, due to the high accuracy of disease recognition. So it was necessary to have algorithms that extract important features without complexity, as well as use artificial intelligence networks to obtain high classification accuracy. In this paper, brain tumors (normal, glioma, meningioma) were identified by proposing the GLCM algorithm to extract the texture features of magnetic resonance images from the radon transform, and after obtaining the important features, they were passed to the proposed networks (SVM, MLPNN and RBFNN) for feature classification and tumor image recognition.

The importance of using the Radon transform is that it reconstructs the original image of the MRI of the brain through the reverse Radon transform and from several projections from different angles, where the reconstructed image is characterized by high computational efficiency and high image quality. While the importance of the GLCM algorithm is its ability to classify pixels in comparison to neighboring pixels in terms of value, color, density, direction, and homogeneity, so it has the ability to identify brain tumor images, because the tumor image has a density that differs from the density of the rest of the brain image, so there will be a change in homogeneity with the rest of the images. It will be easier to use GLCM to extract the histological characteristics of the brain. The results of the proposed networks showed varying accuracy, the best being SVM. This paper is organized as follows: In the second section, the relevant literature on tumor recognition is presented. In the third section, the methodology for recognizing tumors was clarified. The results of the proposed methods were listed in the fourth section. Finally, the conclusion of the paper is presented in the fifth section.

2. Related Works

We provide an overview of the literature related to the recognition of brain tumors. There are many studies in this field and we will present some studies related to the algorithms used in the research. Reference [5] proposed a GA algorithm to collect texture features from the gray level system and then pass them to the SVM to recognize brain tumors and it has achieved good results. Reference [6] proposed a fuzzy c-means algorithm to segment images of cancer tumors and achieved high accuracy and quality in image recognition. while reference [7] proposed and compared three methods of segmenting MRI images of brain tumors and found that the modified region gradient magnitude growth technique yielded the best results. The authors of [8] presented a method for detecting tumors using image segmentation and histogram thresholding. Reference [9] proposed a method for recognizing cancer cells by morphological segmentation and achieved good results. In [10] a method classifier was used to identify tumors using an SVM classifier, the images were optimized by changing the threshold value using the sigmoid function, and the features were extracted using GLCM passed to the SVM classifier. The accuracy of the proposed method was 96.51%. Reference [11] presented a detailed study of modern methods and techniques used in segmenting MRI images of brain cancer. In the study [12]

GLCM and Convolutional Neural Network are used to obtain a strong image texture analysis and a high network depth in image data processing classification. In the reference [13], a feature extraction method was proposed using GLCM for brain tumor detection, and the features were passed to a KSVM classifier to classify them into four different classes. In the study [14], tumors were recognized using the tumor image segmentation algorithm, then image features were extracted by GLCM algorithm, and finally, they were passed to PCA to classify tumor images into five classes, and this method achieved an accuracy of 95%.

The authors of [15] suggested using neural networks to identify tumors and classify them into benign tumor or benign tumor, and image features were extracted by GLCM algorithm. The results showed an accuracy of 93.33%. Reference [16] proposed a method for identifying tumors using a probabilistic neural network, where the features of the images were extracted using discrete wavelet shift with GLCM algorithm followed by morphological processes.

In the study [17], a program for diagnosing and identifying brain cancer using ANN was planned and developed. The surface features of tumors were extracted using GLCM algorithm and a mysterious neurological concept was finally established. The authors of the reference [18] proposed a recurrent neural network to identify brain tumors (pituitary, gliomas and meningioma) and the results showed that the proposed recurrent neural network effectively classified brain tumors with an accuracy of 98%. Reference [19] proposed a convolutional neural network to recognize tumors, and the features of brain tumor images were extracted using discrete wavelet transform technology and GLCM, and the results showed an accuracy of 91%. This paper presents the identification of three brain tumors (normal, glioma and meningioma) using three proposed networks (SVM, MLPNN and RBFNN) after extracting texture features for magnetic resonance images using GLCM algorithm after Radon transformation.

3. Methodology

In this section, we will present the method of recognizing brain tumors (normal, glioma and meningioma). The proposed method is illustrated in the following steps: data collection, pre-processing, Radon transformation for MRI images, extracting features using GLCM algorithm, classification of extracted features and recognition of tumors using three proposed networks (MLPNN, RBFNN, and SVM), Finally, the brain tumor is cut from the MRI images of the brain by segmentation algorithm as shown in Figure 2.

3.1 Data Collection

In this phase, 690 MRI brain images were collected and divided into 450 MRIs for training the system (150 MRIs for normal brain and 300 images for two types of abnormal brain (meningioma and glioma)). The testing phase was assigned 240 MRI images.

3.2 Pre-processing

Pre-processing plays a very important role in this system. Median filter is used to remove the noise and unwanted objects from MRI brain image. Color images are converted to grayscale images.

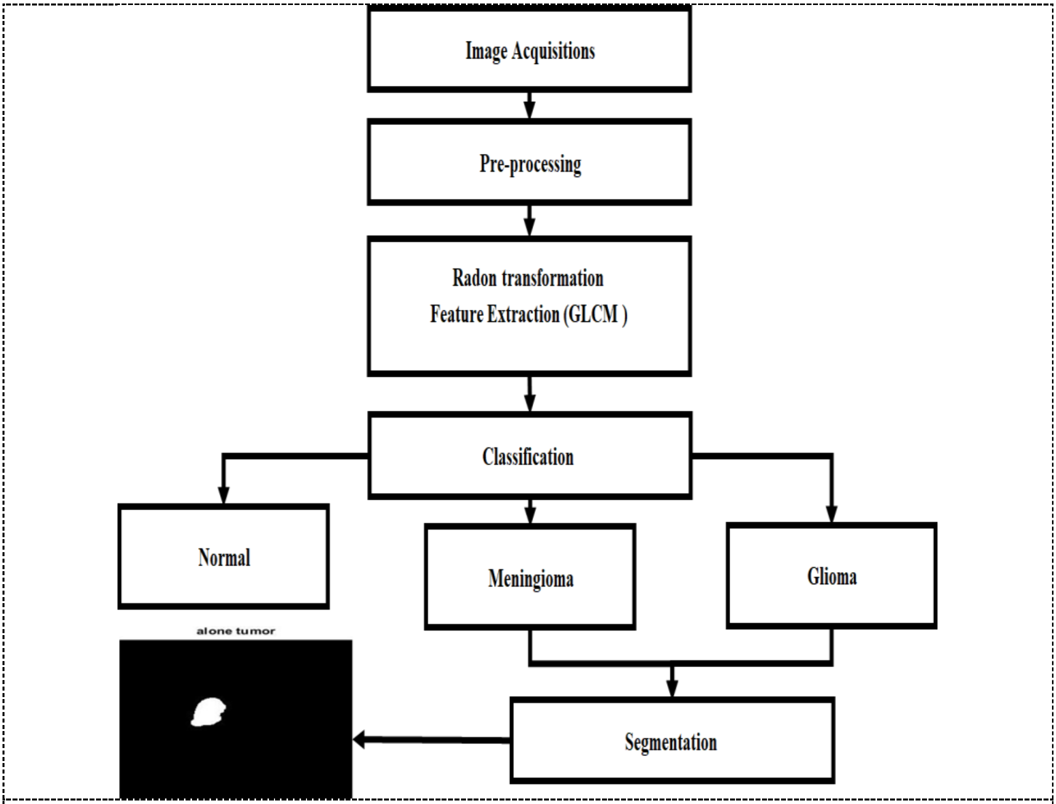
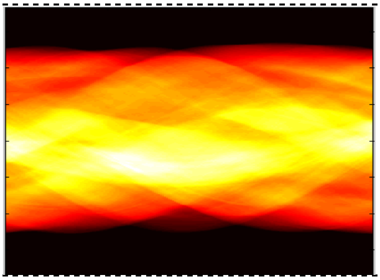


Figure 2. Methodology for brain tumors recognition.

3.3 Feature Extraction

As maintained in the introduction, an important task is extracting the most important features from the images. Features extraction step was done by several stages. The first stage is applying Radon transformation to the MRI image as shown in figure 3.a. In order to select the best projections, we have computed the Radon transform of the MRI images at different projections, then we reconstruct

MRI images by the inverse Radon transform figure 3.b. The best projections are when the reconstruct MRI images (with the inverse Radon transform) is closer to the original image. Reconstructing MRI image using 180 projections gives the closer MRI image to the original image as can be seen in figure 3.


a) Applying Radon transform

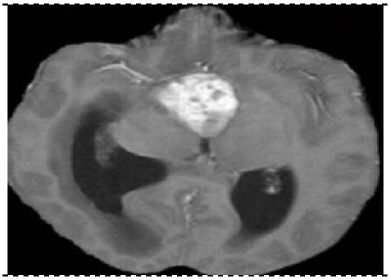

b) Invers Radon

Figure 3. Radon Transformation

After applying Radon transformation, we remove all zeros in order to produce a suitable image with good features. Finally, Gray Level Co-Occurrence Matrix (GLCM) is used to extracted texture features from the Radon transformed brain MRI image. In this paper nine important features are extracted as shown in table 1.

Table 1. GLCM texture feature.

No.	Features	Description	Formula
1	Energy (EN)	The energy is uniformity measurement between the pixels. Range= [0,1].	$\sum_{i,j} p(i,j)^2$
2	Contrast (CO)	Contrast is difference measurement in luminance for making object distinguishable. Range = [0,1]	$\sum_{i,j} \lvert i-j \rvert^2 p(i,j)$
3	Correlation (Cor)	Correlation is the relation measurement between the neighbor pixels. Range = [-1,1].	$\sum_{i,j} \frac{(i,j)p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$
4	Homogeneity (HOM)	The homogeneity measures of closeness of the element distribution in GLCM to GLCM	$\sum_{i,j} \frac{1}{1+(i-j)^2} p(i,j)$

		diagonals. Range = [0,1]	
5	Mean (M)	The mean of an image is calculated by summing of all the pixel values of an image divided by the total number of pixels.	$\left(\frac{1}{m*n}\right)\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} p(i,j)$
6	Standard Deviation (SD)	The Standard describes the possibility distribution of an observed population.	$\sqrt{\left(\frac{1}{m*n}\right)\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} p(i,j) - M^2}$
7	Entropy (E)	Entropy is calculated to characterize the randomness of the textural image.	$-\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} p(i,j)\log_2 p(i,j)$
8	Skewness (SK)	Skewness is a measure of symmetry or the lack of symmetry.	$\left(\frac{1}{m*n}\right)\frac{\sum(p(i,j)-M)^3}{SD^3}$
9	Kurtosis (Kurt)	The shape of a random variable probability distribution is described by the parameter called Kurtosis.	$\left(\frac{1}{m*n}\right)\frac{\sum(p(i,j)-M)^4}{SD^4}$

3.4 CLASSIFICATION

As mentioned in the introduction, SVM, MLPNN and RBFNN were used for classification of brain tumors in MRI images. Brief explanation of these algorithms is described in the following sections.

1. Support Vector Machine: SVM is utilized which is powerful supervised machine learning techniques for classification and regression as shown in Figure 4. Simply stated, the SVM identifies the best separating hyper plane between the two classes of the training samples within the feature space by focusing on the training cases placed at the edge of the class descriptors.

SVM have several kernel functions. In this work we used three different kernel functions (linear. radial basis and quadratic kernel function).

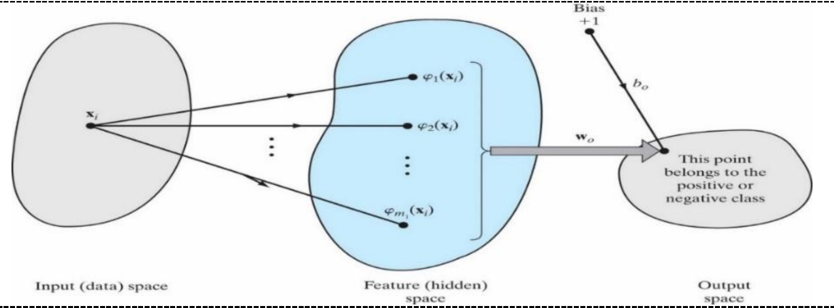


Figure 4. Architecture of support vector machine for pattern classification

2. Multilayer Perceptron Neural Network

A multilayer perceptron neural network is feed-forward neural network (Figure 5) which consists of at least three layers of nodes: an input layer, at least one hidden layer and an output layer [20,21]. MLP Networks are sensitive to the number of neurons in their hidden layers. In this paper, the optimum number of neurons in the hidden layer of MLPNN was investigated from 1 to 9 neurons. Increasing number of neurons in the hidden layer more than 9 neurons the performance of the brain tumors classification takes more time for training the dataset and performance do not increase.

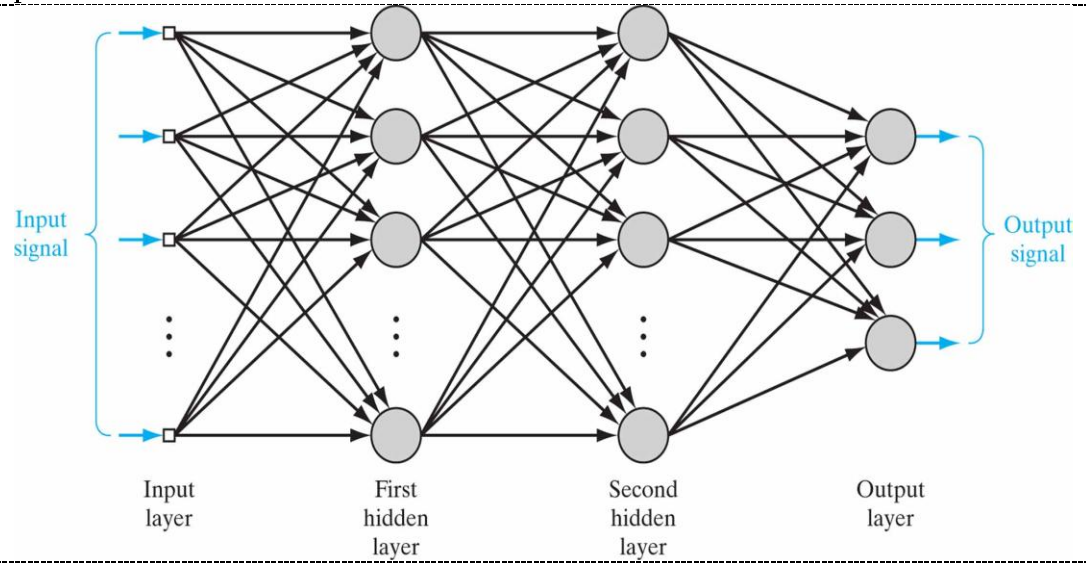


Figure 5. Architecture of multilayer perceptron neural network

3. Radial Basis Function Neural Network

Radial basis function neural network is also a feed-forward network with three different layers: an input layer, a hidden layer and an output layer [22, 23]. Figure 6 shows the structure of the Radial basis function neural network.
The most important part in training RBFNN is determining a spread parameter. The way that the optimum number of this parameter was found is by investigating different RBFNN with various values of spread parameter. The performances of these RBFNN are computed and the value of spread parameter that gives the best performance was selected.

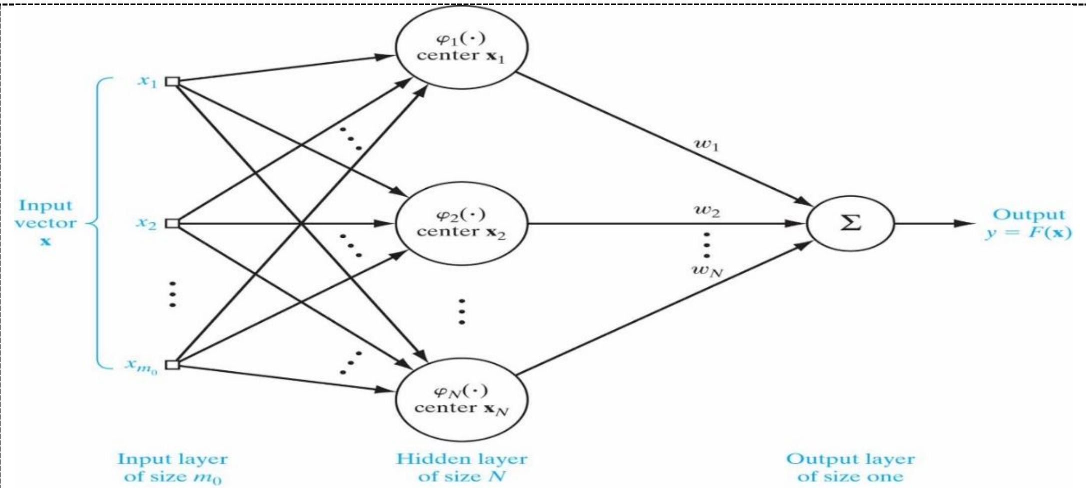


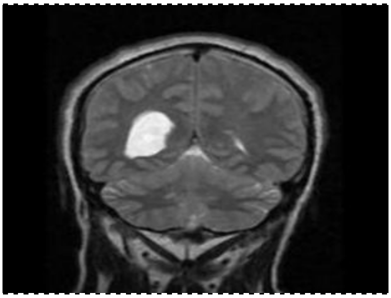
Figure 6. Structure of an RBF network

3.5 SEGMENTATION

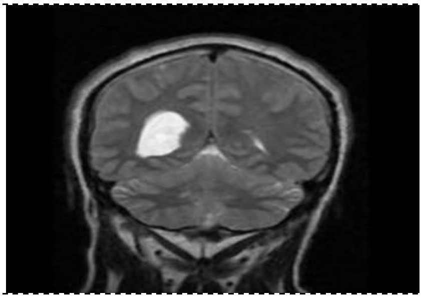
In this part, we will explain the process of brain tumor recognition and diagnosis by segmentation algorithm. First we apply median filter to the gray-scale image and then use edge detection to define the boundaries of the brain MRI image using the Sobel gradient filter and add the result of the Sobel filter to the median filter to get a sharper image as shown in Figure s (7.a and 7.b). After that, various image processing techniques were applied to the MRI brain image in order to cut the tumor image from the original image of the brain. The images are converted into a binary image with a threshold as shown in Figure 7.c. And then converted into a labeled image (Figure 7.d) that returns the label matrix containing the labels of the connected objects present in the binary image. The area and stiffness of each label in the image is then calculated. The area and stiffness of each label in the image is then calculated. These followed steps are repeated with morphological functions such as dilation to obtain the segmented tumor image as shown in Figure 7.

4. Results

In this section, we will present the results obtained during the process of recognizing brain tumors using the proposed networks (SVM, MLPNN and RBFNN). To evaluate the performance of the proposed networks, three measures were used: sensitivity, specificity, and accuracy.

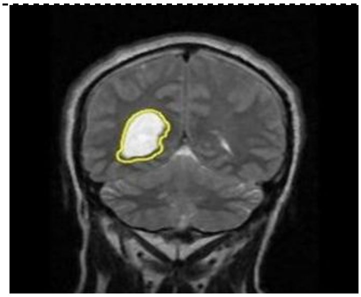


a) Image with median filter



b) Image after Median and sobel filter

c) Binary image



d) Labelled image

e) Segmented tumor

Figure 7. Segmentation algorithm

A. Support Vector Machine

In this part, we will show the results obtained after executing the SVM classifier where we split the dataset into two parts, 450 MRI images for the training phase and 240 for the testing phase. Nine texture features of the GLCM algorithm were extracted after radon transformation of images and passed to the SVM classifier with different kernel functions (Linear, RBF and quadratic) which gave different results and the best performance of quadratic Kernel was achieved (sensitivity, specificity and accuracy is 98.45, 98.97 and 98.71 respectively) as shown in table 2.

Table 2. Classification by SVM with different kernel functions.

Kernel functions	Sensitivity	Specificity	Accuracy
linear	95.42	97.70	96.57
RBF	96.67	98.33	97.5
Quadratic	98.45	98.97	98.71

B. Multilayer Perceptron Neural Network

For multiple neural networks, performance was measured with different number of neurons in the hidden layer. The results obtained by changing the number of neurons were different and the best network performance (sensitivity, specificity and accuracy) was (97.92, 98.95 and 98.44, respectively) at 8 or 9 neurons in the hidden layer as shown in Figure 8 and table 3.

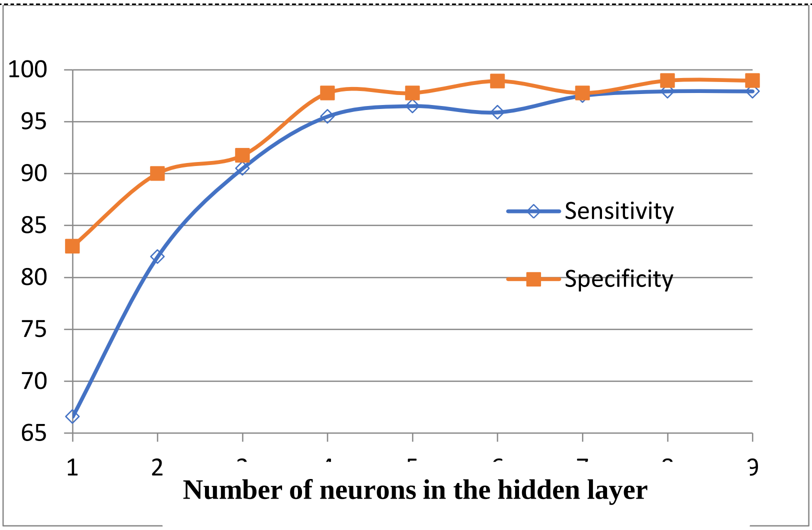


Figure 8. Relation between number of neurons in the hidden layer and sensitivity and specificity.

Table 3. Classification by MLPNN

Number of neurons in the hidden layer	Sensitivity	Specificity	Accuracy
8-9	97.92	98.95	98.44

C. Radial Basis Function Neural Network

Finally, the results obtained from the radial-based neural network, where the performance was measured with the values of different spread parameters, and we got the best value for performance at the spread value of 12, where it achieved (97.5, 98.75, 97.5) for the performance measures (sensitivity, specificity, and accuracy, respectively) as shown in Figure 9 and table 4.

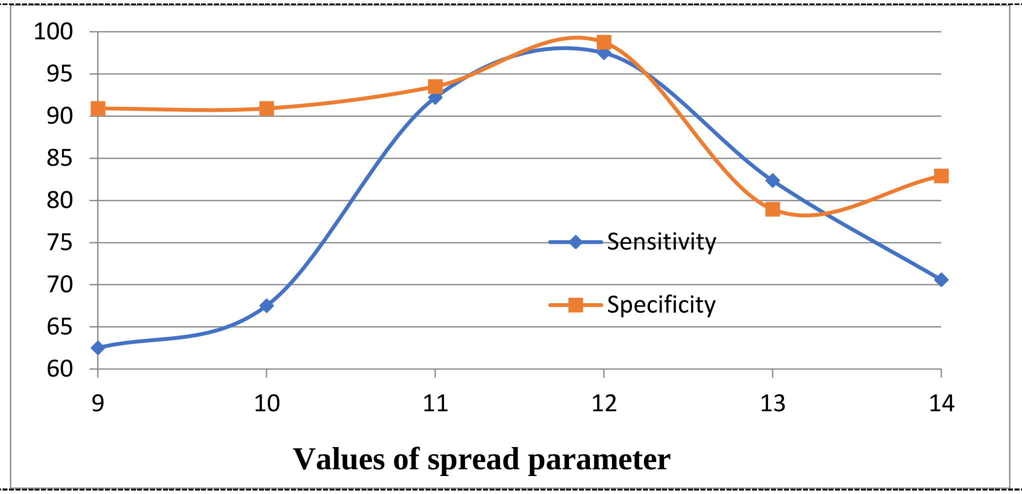


Figure 9. Relation between values of spread parameter and sensitivity and specificity.

Table 4. Classification by RBFNN.

Spread	Sensitivity	Specificity	Accuracy
12	97.5	98.75	97.5

Table 5 presents the performance measures results for the proposed networks (SVM, MLPNN and RBFNN) to recognize brain tumors, and the best results obtained by SVM with quadratic Kernel functions were 98.45, 98.97 and 98.71 for sensitivity, specificity, and accuracy, respectively.

Table 5. The performance of the proposed models.

Classifier	*Parameters*	*Sensitivity%*	*Specificity%*	*Accuracy%*
SVM	linear	95.42	97.70	96.57
	RBF	96.67	98.33	97.5
	Quadratic	98.45	98.97	98.71
MLP	The number of neurons in the hidden layers (8-9)	97.92	98.95	98.44
RBFNN	Spread parameters (12)	97.5	98.75	97.5

5. Conclusions

In this paper, brain tumors were recognized and classified into three classes (normal, glioma and meningioma) by the proposed networks (SVM, MLPNN and RBFNN) after passing them nine features that were extracted from the Gray Level Co-Occurrence Matrix algorithm after radon transformation of the images, the brain tumor was extracted from the magnetic resonance image and the segmentation algorithm and morphology processes were applied to the images.
The performance metrics of the proposed networks (SVM, MLPNN and RBFNN) were compared for the best algorithm to recognized and classify brain tumors based on accuracy, specificity, and sensitivity. The results showed that SVM using quadratic Kernel functions has better performance than MLPNN and RNFNN as it achieved 98.45, 98.97 and 98.71 for sensitivity, specificity, and accuracy, respectively.

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التعرف على أورام المخ باستخدام تحويل الرادون وخوارزمية مصفوفة التواجد المشترك ذات المستوى الرمادي

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المستخلص: حظي مجال التعرف على أورام المخ في السنوات الأخيرة باهتمام واسع من قبل الباحثين في هذا المجال بسبب الانتشار السريع للمرض. في هذا البحث، تم التعرف على أورام الدماغ (طبيعية، ورم دبقي، وورم سحائي) من خلال الشبكات المقترحة (آلة المتجهات الداعمة، والشبكة العصبية متعددة الطبقات Perceptron والشبكة العصبية للوظيفة الشعاعية). تنقسم مجموعة البيانات إلى جزأين: 450 صورة بالرنين المغناطيسي لمرحلة التدريب و150 صورة لمرحلة الاختبار. تم تطبيق المعالجة المسبقة على الصور المدخلة عن طريق تحويل الصور إلى درجات رمادية وإزالة الضوضاء عليها بواسطة مرشح متوسط. بعد ذلك، تم استخراج سمات نسيج صور التصوير بالرنين المغناطيسي باستخدام خوارزمية مصفوفة التواجد المشترك ذات المستوى الرمادي بعد تحويل الرادون. تم تمرير ميزات النسيج المستخرج إلى الشبكات المقترحة لتصنيف الأورام والتعرف عليها. تمت إضافة تقنية استخلاص أورام المخ من صورة الرنين المغناطيسي بواسطة خوارزمية التجزئة وعمليات التشكل على الصور. تم قياس أداء آلة المتجهات الداعمة، والشبكة العصبية متعددة الطبقات Perceptron والشبكة العصبية للوظيفة الشعاعية بناءً على الحساسية والنوعية والدقة وأفضل النتائج التي تم الحصول عليها بواسطة SVM مع وظيفة النواة التربيعية كانت 98.45 و98.97 و 98.71 للحساسية والنوعية، والدقة، على التوالي.

الكلمات المفتاحية: الشبكة العصبية متعددة الطبقات الإدراكية، آلة ناقلات الدعم، وظيفة الأساس الشعاعي للشبكة العصبية، مصفوفة التواجد المشترك ذات المستوى الرمادي، تحويل الرادون، التصوير بالرنين المغناطيسي.

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